Syllabus

STAT 648

Graphical Models and Networks

Credits: 3

Meeting dates, times, and places

Dates: Tuesday, Thursday, January 13—April 23 with the exception of

- Thursday, January 29
- Tuesday, March 3: Spring break
- Thursday, March 5: Spring break
- Thursday, April 2: Midterm recess

Times: see the website of the Office of the Registrar.

Places: see the website of the Office of the Registrar.

Instructor

Name: Dr. Michael Schweinberger

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Teaching assistant

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Course objectives

Graphical models—aka Markov networks and Bayesian networks—have been widely used to represent complex phenomena with dependence. The course aims to

- stimulate interest in graphical models.
- provide students with a background in graphical models, theory, methods, and applications.

Course outcomes

There are at least three expected learning outcomes. First, students are expected to be able to construct graphical models, develop statistical procedures for estimating the structure and the parameters of graphical models, apply the statistical procedures to real-world data, and interpret the results. Second, students are expected to be able to evaluate the statistical procedures developed by other researchers and the results obtained by them. Third, students are expected to be able to understand and communicate the properties of statistical procedures.

Course structure

The course is divided into two parts:

- Instruction (weeks 1–12): see course contents.
- Seminar (weeks 13–15): students form groups based on shared interests and choose topics of interest. The groups conduct either original research on the chosen topic (which can be applied, computational, or theoretical) or compile a survey of the literature on the chosen topic; results are presented and discussed in class.

Course books

It is not required, but recommended to supplement lectures by reading one or more books. Some possible books are:

- Classics: Pearl (1988) in artificial intelligence and Lauritzen (1996) in classic statistics.
- Main course book in computer science: Koller and Friedman (2009); classic alternatives: Pearl (1988); Castillo, Gutiérrez, and Hadi (1997); Cowell (1999); Borgelt and Kruse (2002); modern alternatives: Bishop (2007) and Wainwright and Jordan (2008).
- Main course book in statistics: Lauritzen (1996); classic alternatives: Whittaker (2009); modern alternatives: Hastie, Tibshirani, and Friedman (2011); Bühlmann and van de Geer (2011).
- Modern statistics: Hastie, Tibshirani, and Friedman (2011) (applied, computational) and Bühlmann and van de Geer (2011) (theoretical).
- Bayesian networks: Koski and Noble (2009); alternatives: Højsgaard, Edwards, and Lauritzen (2012); Nagarajan, Scutari, and Lébre (2013); Scutari and Denis (2015).
- Applications: Edwards (2000); Højsgaard et al. (2012); Nagarajan et al. (2013); Taroni et al. (2014); Scutari and Denis (2015).

Course contents

- Graphical models: graphs representing conditional independence relations among random variables:
  - Markov properties.
  - Undirected graphical models (Markov networks).
  - Directed graphical models (Bayesian networks).
  - Graphical models as exponential families.
  - Decomposable graphical models (including trees).
  - Example: Ising model (e.g., physics).
  - Example: Markov random field (e.g., image processing, spatial statistics).

  - Example: Markov random graph models (e.g., social networks).
  - Example: Markov chains (countless applications).
  - Example: Gaussian graphical models (countless applications).
- Local computing in graphical models (e.g., junction tree algorithm).
- Statistical learning of graphical models:
  - Model selection: learning the structure of graphs.
  - Model estimation: learning the parameters given the structure of graphs.
- Low-dimensional statistical learning of graphical models.
- High-dimensional statistical learning of graphical models.
- Bayesian approaches to statistical learning.
- Applications: can be chosen as final project.

Grades

- Homeworks: 30%
- Midterm: 30%
- Final project: 40%
- Bonus: participation: 5%

Homeworks must be submitted at the beginning of the class on the due date. Late homeworks will be accepted, but the grades of late homeworks are discounted by factor 0.5 every 12 hours. The lowest homework grade will be dropped. The midterm exam will be open-book and take-home. The final projects can be conducted by groups of students which are formed based on shared interests and choose topics of interest. The groups conduct either original research on the chosen topic (which can be applied, computational, or theoretical) or compile a survey of the literature on the chosen topic; results are presented and discussed in class.

Attendance

Attendance of classes is not required, but recommended.

Honor Code

The course is governed by the Honor Code of Rice University.

Disabilities

If you have a documented disability that will impact your work in class, contact the instructor. In addition, you need to be registered with Disability Support Services Office in the Allen Center. The policy of Rice University regarding disabilities are observed: see http://ga.rice.edu/.

Other policies

All other policies of Rice University are observed: see http://ga.rice.edu/.

REFERENCES

Bishop, C. (2007), *Pattern Recognition and Machine Learning*, New York: Springer.

Borgelt, C., and Kruse, R. (2002), *Graphical Models: Methods for Data Analysis and Mining*, New York: Wiley.

Bühlmann, P., and van de Geer, S. (2011), *Statistics for High-Dimensional Data: Methods, Theory and Applications*, New York: Springer.

Castillo, E., Gutiérrez, J. M., and Hadi, A. S. (1997), *Expert systems and probabilistic network models*, New York: Springer.

Cowell, R. (1999), *Introduction to inference for Bayesian networks*, Cambridge, MA: MIT Press.

Edwards, D. (2000), *Introduction to Graphical Modelling*, New York: Springer.

Hastie, T., Tibshirani, R., and Friedman, J. (2011), *The Elements of Statistical Learning*, New York: Springer, 2nd ed.

Højsgaard, S., Edwards, D., and Lauritzen, S. (2012), *Graphical Models with R (Use R!)*, New York: Springer.

Koller, D., and Friedman, N. (2009), *Probabilistic Graphical Models. Principles and Techniques*, Cambridge, Massachusetts: MIT Press.

Koski, T., and Noble, J. M. (2009), *Bayesian Networks: An Introduction*, Chichester: Wiley.

Lauritzen, S. (1996), *Graphical Models*, Oxford, UK: Oxford University Press.

Nagarajan, R., Scutari, M., and Lébre, S. (2013), *Bayesian Networks in* `R`, New York: Springer.

Pearl, J. (1988), *Probabilistic Reasoning in Intelligent Systems: Networks of Plausible Inference*, San Francisco: Morgan Kaufmann.

Scutari, M., and Denis, J. B. (2015), *Bayesian Networks With Examples in* `R`, Boca Raton: CRC Press.

Taroni, F., Biedermann, A., Bozza, S., Garbolino, P., and Aitken, C. (2014), *Bayesian Networks for Probabilistic Inference and Decision Analysis in Forensic Science*, Chichester: Wiley.

Wainwright, M. J., and Jordan, M. I. (2008), "Graphical models, exponential families, and variational inference," *Foundations and Trends in Machine Learning*, 1, 1–305.

Whittaker, J. (2009), *Graphical Models in Applied Multivariate Statistics*, New York: Wiley.